ISSN 2723-6471

An Extensive Exploration into the Multifaceted Sentiments Expressed by Users of the myIM3 Mobile Application, Unveiling Complex Emotional Landscapes and Insights

B Herawan Hayadi[1], Henderi[2,*], Mukti Budiarto[3], Sofa Sofiana[4], Padeli[5], Didik Setiyadi[6], Rulin Swastika[7], Rita Wahyuni Arifin[8]

[1]Primary School Teacher Education, Universitas Bina Bangsa, Serang, Indonesia

[2,3,5] Informatics Engineering, University of Raharja, Tangerang 15117, Indonesia

[4] Faculty of Computer Science, Informatics Engineering, Universitas Pamulang, Tangerang 15417, Indonesia

[6] Information Systems, STMIK Sinar Nusantara, Surakarta 57149, Indonesia

[7]Study Program of Informatics Engineering, Universitas Al-Khairiyah, Cilegon 42441, Indonesia

[8]Informatics Management Bina Insani University, Bekasi 17114, Indonesia

(Received: March 22, 2024; Revised: March 26, 2024; Accepted: April 4, 2024; Available online: May 17, 2024)

Abstract

This study investigates user sentiment towards the myIM3 application, an application used for telecommunication service management in Indonesia. Using text analysis and machine learning methods, we analyzed user reviews to identify dominant sentiment patterns and evaluate different classification models. Word cloud analysis, sentiment distribution, and donut plots were utilized to gain deeper insights into user preferences and issues. Results indicate that the majority of user reviews are neutral (52.2%), with 37% positive reviews and 33.4% negative reviews. Users consistently pay attention to aspects such as internet connection (Neutral: 92%, Positive: 95%, Negative: 87%) and pricing (Neutral: 92%, Positive: 92%, Negative: 93%) in their reviews. Evaluation of classification models like Decision Tree Classifier, Support Vector Machine (SVM), and Random Forest shows that the SVM model performs the best with an accuracy of 93%, high precision (Negative: 93%, Neutral: 92%, Positive: 95%), recall (Negative: 93%, Neutral: 95%, Positive: 91%), and F1-score (Negative: 93%, Neutral: 94%, Positive: 93%). These findings can serve as a basis for service improvement and better product development in the future, while also affirming the capability of text analysis and machine learning techniques in providing valuable insights for telecommunication service providers.

Keywords: User sentiment analysis, Machine learning, Text analysis, Sentiment patterns, Support Vector Machine (SVM)

1. Introduction

In today's digital age, mobile applications have revolutionized the way we interact with technology, offering a myriad of services at our fingertips [1]. Among these applications, those catering to telecommunications needs hold particular significance, providing users with essential functionalities such as managing data usage, monitoring account balances, and accessing promotional offers [2]. In this landscape, understanding user sentiments towards these applications is not only beneficial but also imperative for service providers striving to deliver exceptional user experiences [3].

One such telecommunications application that has garnered substantial user attention is myIM3, a versatile platform widely used in Indonesia for managing telecommunication services [4]. As users increasingly rely on mobile applications for their day-to-day activities, the myIM3 app serves as a central hub for users to navigate their telecommunication needs efficiently. From purchasing data packages to accessing account information and availing themselves of promotional deals, myIM3 offers a comprehensive suite of services aimed at simplifying the telecommunications experience for its users.

***Corresponding author: Henderi (henderi@raharja.info)**
DOI: https://doi.org/10.47738/jads.v5i2.187

Recognizing the pivotal role of user satisfaction and loyalty in the success of telecommunications service providers, gaining insights into user sentiments towards the myIM3 application emerges as a critical endeavor [5]. By delving into the multifaceted landscape of user sentiments, service providers can glean invaluable insights into user preferences, pain points, and areas of satisfaction, thus informing strategic decisions aimed at enhancing the overall user experience.

Against this backdrop, this research embarks on an in-depth exploration of user sentiments expressed towards the myIM3 mobile application. Leveraging advanced text analysis techniques and machine learning algorithms [6], [7], delve into user reviews to uncover nuanced sentiments and discern underlying patterns. Through this rigorous analysis, we seek to unveil the intricate emotional landscapes traversed by users, shedding light on both positive sentiments that reinforce user satisfaction and negative sentiments that signal areas in need of improvement.

The significance of this study extends beyond mere academic curiosity; it holds practical implications for telecommunications service providers seeking to optimize their offerings and elevate user experiences. By dissecting user sentiments with precision and granularity, we aim to provide actionable insights that enable service providers to fine-tune their strategies, refine their applications, and cultivate stronger relationships with their user base. In the subsequent sections of this paper, we embark on a comprehensive journey, unraveling the complex tapestry of user sentiments expressed towards the myIM3 application. Through meticulous analysis and interpretation, we aim to unearth invaluable insights that pave the way for enhanced service provision and enriched user experiences.

2. Literature Review

Understanding user sentiments towards mobile applications has been a topic of growing interest in recent years, driven by the increasing reliance on mobile technology in various aspects of daily life [8]. While extensive research has been conducted in sentiment analysis across different domains, including e-commerce, social media, and entertainment, the telecommunications sector presents its own unique challenges and opportunities [10], [11]. In the realm of mobile telecommunications applications, user sentiments play a crucial role in shaping user satisfaction, loyalty, and ultimately, the success of service providers [12], [13]. Therefore, researchers have increasingly turned their attention towards analyzing user sentiments in this context to uncover insights that can inform strategic decision-making and service improvements.

Several studies have investigated the factors influencing user sentiments towards mobile telecommunications applications [14]. Key aspects such as usability, functionality, pricing, network reliability, and customer support have emerged as significant determinants of user satisfaction. For example, research by Zhang et al. [14], found that users prioritize ease of navigation and transaction processes when evaluating mobile applications, highlighting the importance of user-friendly interfaces in driving positive sentiments. Furthermore, pricing and affordability have been identified as critical factors affecting user perceptions of value and satisfaction. Studies by Yun et al. [15], and Aksoy et al. [16], demonstrated that users are highly sensitive to pricing structures and are more likely to express negative sentiments towards applications perceived as offering poor value for money.

Network reliability and performance also play a pivotal role in shaping user sentiments towards telecommunications applications. Poor network connectivity, slow data speeds, and frequent service disruptions often lead to user frustration and dissatisfaction. Research conducted by Garín-Muñoz, et al. [17], highlighted the strong correlation between network quality and user sentiments, underscoring the importance of robust infrastructure in maintaining user satisfaction. In addition to functional aspects, the quality of customer support services offered by telecommunications providers significantly influences user sentiments. Studies by Kang et al. [18] and Chen et al. [19], revealed that prompt resolution of user queries and complaints positively impacts user perceptions of service quality and enhances overall satisfaction. While existing literature provides valuable insights into the factors influencing user sentiments towards mobile telecommunications applications, there remains a need for more comprehensive studies focusing specifically on management applications like myIM3. By addressing this research gap, the present study aims to contribute to the existing body of knowledge and provide actionable insights for telecommunications service providers striving to improve user experiences and satisfaction.

ISSN 2723-6471

3. Method

In this section, we outline the methodology employed in our study to analyze user sentiments expressed in reviews of the myIM3 mobile application. The methodology encompasses data collection, preprocessing, exploratory data analysis (EDA), feature extraction, model selection and training, model evaluation, and interpretation of results [20]. Figure 1 show for each step is meticulously designed to ensure a systematic and comprehensive approach towards understanding user sentiments and deriving actionable insights from the dataset.

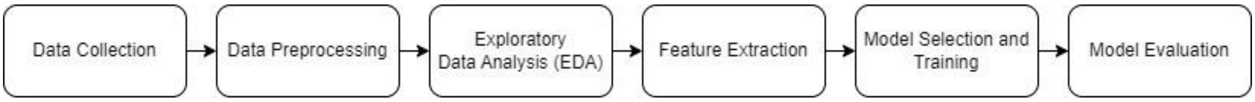

Figure 1. Research step

3.1. Data Collection

The first step in conducting sentiment analysis of user reviews for the myIM3 application involves data collection. We obtained a dataset comprising user reviews from various sources, including app stores, online forums, and social media platforms. The dataset encompasses a diverse range of reviews, capturing user sentiments and opinions towards different aspects of the myIM3 application.

3.2. Data Preprocessing

Following the data collection phase, the gathered information undergoes preprocessing to ensure its consistency and suitability for analysis. This crucial stage involves several essential procedures aimed at refining the raw textual data [21]. Initially, techniques for text normalization are applied to standardize the text, such as converting all text to lowercase, eliminating punctuation marks, and managing abbreviations to maintain uniformity throughout the dataset. Subsequently, tokenization is conducted to segment the text into individual words or tokens, facilitating the organization and manipulation of the textual data for subsequent analysis.

Additionally, common stopwords, which lack significant meaning in sentiment analysis contexts, are eliminated from the text to reduce noise and concentrate on words more pertinent to the analysis. Finally, lemmatization or stemming techniques are utilized to reduce words to their base or root forms, thereby consolidating variations of the same word and simplifying the analysis process while enhancing sentiment classification accuracy. Through the implementation of these preprocessing methods, the dataset is effectively refined and primed for further analysis, ensuring its suitability for extracting meaningful insights regarding user sentiments expressed in reviews of the myIM3 mobile application.

3.3. EDA

EDA serves as a crucial preliminary step in understanding the underlying structure and patterns within the dataset [20]. In our study, we conducted a comprehensive exploratory analysis to gain deeper insights into the characteristics and distribution of sentiments expressed by users in their reviews of the myIM3 mobile application. To begin with, we employed various visualization techniques to elucidate the inherent patterns and trends present in the dataset. Word frequency distributions were generated to identify the most commonly occurring words and phrases across the reviews. This allowed us to discern prevalent themes and topics that were frequently discussed by users.

Additionally, word clouds were constructed to visually represent the relative frequency of words in the dataset, with larger font sizes indicating higher frequencies. This graphical representation provided a succinct overview of the most prominent terms and sentiments prevalent in the reviews. Furthermore, sentiment histograms were utilized to visualize the distribution of sentiments within the dataset. By plotting the frequency of positive, negative, and neutral sentiments, we were able to ascertain the overall sentiment distribution and identify any potential biases or imbalances in the dataset.

Through these exploratory analyses, we gained valuable insights into the sentiment landscape of the myIM3 mobile application. The visualizations enabled us to identify common themes, sentiment patterns, and prevalent topics discussed by users, laying the groundwork for further in-depth analysis and interpretation of the dataset.

3.4. Feature Extraction

During the feature extraction phase, our primary goal was to convert the processed text data into numerical formats suitable for machine learning algorithms [22]. This step is pivotal since the majority of machine learning algorithms operate on numerical data rather than raw text. To accomplish this, we utilized various techniques tailored for effective handling of text data. One of the key methods employed is the bag-of-words (BoW) model, where each document is represented as a vector, with each dimension corresponding to a unique word in the corpus. The value of each dimension indicates the frequency of the respective word in the document. By constructing a vocabulary from the entire corpus and representing each document using this vocabulary, we create numerical feature vectors that capture word occurrence patterns across documents. Additionally, we incorporated the term frequency-inverse document frequency (TF-IDF) approach, which evaluates the significance of a word in a document relative to its occurrence in the entire corpus. This method assigns higher weights to words that are common in a specific document but rare across the corpus, thereby highlighting the discriminative power of such words in characterizing document content.

Moreover, we investigated the utilization of word embeddings like Word2Vec or GloVe to capture semantic relationships and contextual information embedded within the text. Word embeddings represent words as dense, low-dimensional vectors in a continuous vector space, where words with similar meanings or contexts are positioned closer to each other. By leveraging pre-trained word embeddings or training custom embeddings on our dataset, we aimed to capture the nuanced semantic meanings and associations inherent in the text data. Through the integration of these diverse feature extraction techniques, our objective was to produce comprehensive numerical representations of the text data, facilitating the effective capture of underlying patterns and nuances in user-generated reviews of the myIM3 mobile application. These feature representations serve as the foundation for training machine learning models to accurately classify user sentiments.

3.5. Model Selection and Training

Our research employs various machine learning algorithms to develop sentiment classification models using features extracted from a preprocessed dataset. These models are essential for accurately predicting user sentiment towards the myIM3 mobile application. We investigate several popular algorithms, each with distinct advantages suited to our classification objectives.

Decision trees are frequently chosen for classification tasks due to their straightforward nature and capability to handle diverse data types [23]. This algorithm divides the feature space into regions, making decisions based on feature values at each node. Classification involves traversing the tree from the root to a leaf node, where the final decision is made. The splitting criterion, such as Gini impurity or information gain, determines the feature used for splitting at each node.

Decision Tree Formula [23]:

Gini impurity: $Gini(D) = 1 - \sum_{i=1}^{c} P_i^2$ (1)

Information gain: $IG(D, A) = H(D) - \sum_{v=1}^{V} \frac{|D_v|}{|D|} H(D_v)$ (2)

The Support Vector Machine (SVM) emerges as a robust tool for binary classification assignments, adept at crafting hyperplanes to differentiate data instances belonging to distinct classes with utmost margin [24]. Its functionality revolves around transforming input data into a feature space of higher dimensions, where class distinctions can be delineated by a hyperplane. The selection of the optimal hyperplane hinges on the dual objective of maximizing inter-class margin while concurrently minimizing classification inaccuracies.

SVM Formula [24]:

Hyperplane equation: $w^T x + b = 0$ (3)

Margin: $\frac{2}{||w||}$ (4)

Soft margin: $min_{w,b,\varepsilon} \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} \varepsilon_i$ (5)

 ISSN 2723-6471

The Random Forest technique is a form of ensemble learning, where it builds numerous decision trees in the training phase and yields the most frequently occurring class (for classification) or the average prediction (for regression) of the individual trees [25]. This method combats overfitting and boosts accuracy by amalgamating the predictions from multiple trees. Each tree within the forest is trained on a random subset of both the training data and its features.

Random Forest Formula [25]:

$$\text{Bagging: } \hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{*b}(x) \tag{6}$$

In recent times, there has been a surge in the popularity of neural networks, especially deep learning models, owing to their capacity to grasp intricate patterns and representations from datasets [26]. These models are comprised of layers of interconnected neurons, wherein each layer undertakes transformations on the input data. Notably, deep neural networks like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have showcased exceptional capabilities across a spectrum of natural language processing endeavors, encompassing tasks such as sentiment analysis.

Neural Network Formula [26]:

$$\text{Forward propagation: } z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]} \tag{7}$$

$$\text{Activation function: } a^{[l]} = g^{[l]}(z^{[l]}) \tag{8}$$

$$\text{Backpropagation: } z^{[l]} = dA^{[l]} \times g^{[l]\prime}(z^{[l]}) \tag{9}$$

The dataset undergoes segmentation into training and testing sets for the facilitation of model training and assessment. Techniques for hyperparameter optimization, like grid search or randomized search, are implemented to enhance the efficacy of each algorithm. Through meticulous model selection and training, our goal is to construct sentiment classification systems for the myIM3 mobile application that are both resilient and precise.

3.6. Evaluation of Models:

The performance of the trained models is assessed using suitable evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics offer insights into the models' proficiency in accurately categorizing sentiments. Furthermore, methods such as cross-validation may be utilized to gauge the models' resilience and ability to generalize to new data.

4. Result and Discussion

4.1. Sentiment Analysis of myIM3 Users

The initial step of this examination employs the word cloud method to showcase the prevalent words found in the reviews provided by users of myIM3, categorized into neutral, positive, and negative sentiments. A word cloud visually represents the frequency of words within a dataset, with larger words indicating higher occurrence rates. The objective of this examination is to discern prevalent patterns in user responses regarding the application. Figure 2 exhibits the word clouds representing neutral, positive, and negative sentiments generated from the dataset.

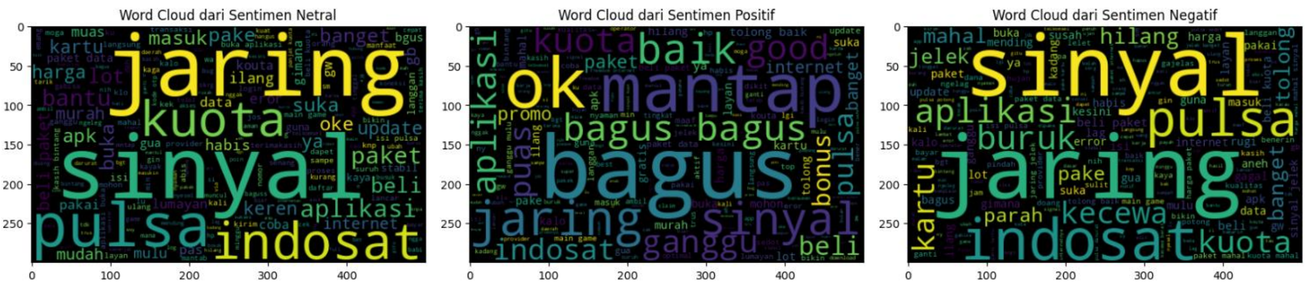

Figure 2. Word Cloud of Neutral, Positive, and Negative Sentiments

The analysis results indicate that in neutral reviews, frequently appearing words tend to relate to functional aspects of the application such as internet connection, price, and application features. Users in this category may express reviews with a neutral tone, indicating a moderate satisfaction with the service without giving extremely positive or negative ratings. On the other hand, in positive reviews, it was found that dominating words often relate to praise for the ease of using the application, affordable prices, and good internet connection speed. This indicates that users giving positive feedback are likely very satisfied with their experience using the myIM3 application, and they highlight the positive aspects of the service.

Meanwhile, in negative reviews, words related to complaints about poor internet connection quality, perceived high prices, or other technical issues were found. Users expressing negative sentiments in their reviews may experience dissatisfaction or disappointment with the service they received, and they use their reviews to express their concerns or dissatisfaction. Thus, the results of this word cloud analysis provide deep insights into the aspects most noticed by users in the myIM3 application, as well as understanding of user preferences and needs that can serve as a basis for future development and service improvement.

The next step in this analysis is to explore the sentiment distribution of overall user reviews of myIM3. By examining the proportion of neutral, positive, and negative reviews, the goal of this analysis is to gain a more comprehensive understanding of user perceptions of this application. Figure 3 below depicts the sentiment distribution of myIM3 users.

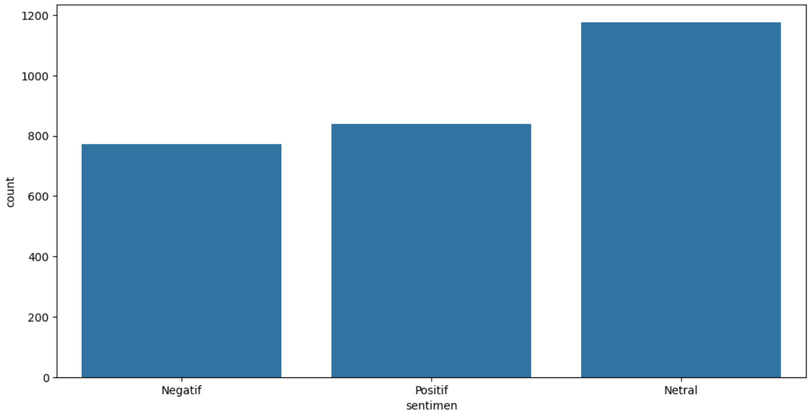

Figure 3. Distribution of Myim3 User Sentiments

From the results of this analysis, it can be seen that the majority of myIM3 user reviews are categorized as neutral sentiment. However, there is also a significant proportion of reviews reflecting positive and negative sentiments. This indicates that while the majority of users may not have strong feelings towards the application, there is also a group of users who are either very satisfied or dissatisfied with the service provided.

To provide a more visual representation of the shift in sentiment distribution from total reviews to positive and negative reviews, a funnel chart was used. Through this visualization, it can be observed how the number of reviews decreases as the sentiment changes from neutral to positive or negative. The funnel chart helps understand the extent to which sentiment changes occur within the range of reviews and allows for the identification of potential areas for improvement. This analysis of sentiment distribution provides a deeper understanding of how users respond to the myIM3 application overall. By understanding this sentiment distribution, companies can direct their efforts to improve user satisfaction and address any issues that may arise.

To gain deeper insights into user sentiment towards the myIM3 application, an analysis was conducted using a donut plot as shown in figure 4. This method allows for the visual analysis of the most frequently occurring words in neutral, positive, and negative reviews, making it easier to understand and interpret the results. This analysis provides an opportunity to discover patterns and preferences that may not be apparent in other analyses.

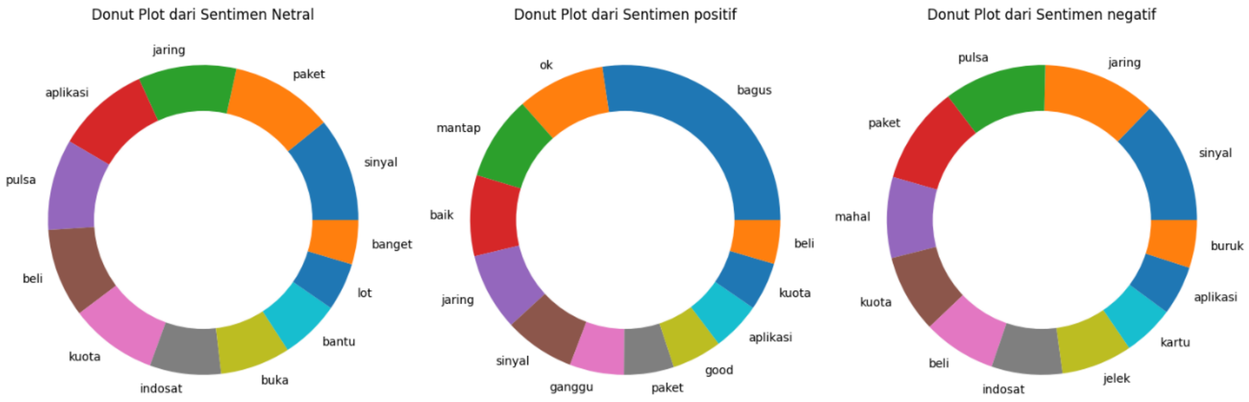

Figure 4. Donut Plot of User Sentiments

Using a donut plot, we can visualize how often key words appear in each sentiment category. For instance, in neutral reviews, words like "network," "signal," and "price" might occur more frequently, whereas in positive reviews, words like "easy," "great," and "fast" might dominate. On the other hand, in negative reviews, we might find words like "expensive," "slow," and "issues" as the most common. Donut plot analysis provides a more detailed understanding of user preferences and complaints regarding the application. It helps identify underlying trends in user feedback and highlights potential areas that need to be addressed or improved in service development. By understanding user sentiment depicted through donut plots, companies can take strategic steps to enhance user satisfaction and improve the overall user experience.

4.2. Model Evaluation

After training on three different classification models, namely Decision Tree Classifier, Support Vector Machine (SVM), and Random Forest, the performance of each model was evaluated. Evaluation was done using several standard performance metrics such as accuracy, precision, recall, and F1-score, to gain a comprehensive understanding of the model's ability to predict user sentiment in myIM3. Table 1 presents the evaluation results of the three tested classification models, namely Decision Tree Classifier (Tuned), Support Vector Machine (Tuned), and Random Forest (Tuned), in predicting user sentiment in myIM3.

Table 1. Evaluation Results

Model	Precision	Recall	F1-Score	Support
Decision Tree Classifier (Tuned)				
Negative	0.89	0.87	0.88	161
Neutral	0.92	0.95	0.93	232
Positive	0.92	0.90	0.91	165
Support Vector Machine (Tuned)				
Negative	0.93	0.93	0.93	161
Neutral	0.92	0.95	0.94	232
Positive	0.95	0.91	0.93	165
Random Forest (Tuned)				
Negative	0.83	0.96	0.89	161
Neutral	0.95	0.94	0.94	232
Positive	0.99	0.86	0.92	165

The adjusted Decision Tree Classifier model shows interesting evaluation results. With an accuracy of 91%, this model succeeds in predicting myIM3 user sentiment effectively. Further analysis of this model's performance metrics reveals some intriguing findings. The high precision rate of 92% for classifying positive sentiment indicates that the model tends to provide accurate predictions when identifying reviews expressing user satisfaction with the myIM3 service.

In other words, when the model classifies a review as positive sentiment, it is highly likely that the review truly reflects user satisfaction with the application.

Moreover, a fairly good recall rate of 95% for neutral sentiment indicates that the model is adept at detecting neutral or unbiased reviews without disregarding the abundance of such sentiment in the dataset. This demonstrates the model's ability to not only focus on strong sentiments but also consider neutral reviews in the classification process. However, it should be noted that the model has a slightly lower recall rate of 87% for negative sentiment, suggesting that the model tends to struggle in recognizing reviews containing criticism or dissatisfaction from users towards the myIM3 service. Although the precision rate for negative sentiment may remain high, it is important to improve recall to make the model more effective in identifying reviews containing negative sentiment.

The adjusted SVM model demonstrates outstanding performance with an accuracy of 93%. This indicates the model's ability to classify myIM3 user sentiment with a high level of accuracy. However, it is important to note that accuracy alone is not sufficient to evaluate the model's performance comprehensively. Therefore, we need to delve deeper into other metrics such as precision, recall, and F1-score to gain a more comprehensive understanding of the model's performance. Further analysis of these metrics indicates that the SVM model has high precision, recall, and F1-score for all sentiment classes. For negative sentiment, SVM achieves a precision of 93%, recall of 93%, and F1-score of 93%. This means that the SVM model tends to provide accurate predictions in identifying reviews containing negative sentiment while minimizing the number of actually positive or neutral reviews misclassified as negative.

For neutral sentiment, the SVM model has a precision of 92%, recall of 95%, and F1-score of 94%. This indicates that the model tends to provide accurate predictions in classifying neutral reviews while considering the majority of neutral reviews in the dataset. As for positive sentiment, SVM achieves a precision of 95%, recall of 91%, and F1-score of 93%. These results indicate that the model consistently identifies reviews containing positive sentiment from myIM3 users. Thus, these overall results indicate the SVM model's ability to generate accurate and consistent predictions in classifying myIM3 user sentiment, as well as demonstrating the potential of this model for practical use in analyzing user sentiment in the application.

Meanwhile, the adjusted Random Forest model also demonstrates good performance with an accuracy of 92%. Although these results indicate satisfactory accuracy, further analysis reveals some interesting aspects regarding the model's performance. The Random Forest model has a slightly lower recall rate for negative sentiment, although still quite high, at 96%. This indicates that the model is better at identifying reviews that truly contain negative sentiment, but there may be some negative reviews that are missed or misclassified as neutral or positive. On the other hand, the model excels in terms of precision rate for positive sentiment, reaching 99%. This indicates that when the Random Forest model classifies a review as positive, it is highly likely that the review indeed contains positive sentiment. This is a good indication of the model's ability to distinguish positive reviews from others. Based on the evaluation results of the three models, it can be concluded that the SVM model demonstrates the best performance in predicting myIM3 user sentiment, followed by the Decision Tree Classifier and Random Forest models. However, the results from the Random Forest model still provide valuable insights into our understanding of user sentiment in the myIM3 application, especially in identifying negative and positive reviews with high precision.

5. Conclusion

In this study, in-depth analysis of user sentiment towards the myIM3 application has been conducted using various text analysis methods and machine learning techniques. Through the use of word cloud techniques, funnel charts, and donut plots, dominant sentiment patterns in user reviews have been successfully identified visually. Evaluation of three different classification models, namely Decision Tree Classifier, SVM, and Random Forest, has been carried out to predict user sentiment. The evaluation results show that the SVM model is the most superior with an accuracy of 93%, followed by the Random Forest model with an accuracy of 92%, and the Decision Tree Classifier model with an accuracy of 91%. The SVM model also demonstrates the best performance in classifying positive, neutral, and negative sentiments with high precision, recall, and F1-score rates. These findings provide valuable insights for telecommunication service providers such as myIM3 in understanding their users' perceptions and preferences. By understanding user sentiment more deeply, companies can identify areas that need to be improved or enhanced in their applications to increase user satisfaction and strengthen their position in the market. Additionally, this research also demonstrates the importance of implementing text analysis techniques and machine learning in understanding user feedback and making more informed decisions in product and service development.

6. Declarations

6.1. Author Contributions

Conceptualization: B.H.H., H., M.B., S.S., P., D.S., R.S., and R.W.A.; Methodology: H.; Software: B.H.H.; Validation: B.H.H., H., M.B., S.S., P., D.S., R.S., and R.W.A.; Formal Analysis: B.H.H., H., M.B., S.S., P., D.S., R.S., and R.W.A.; Investigation: B.H.H.; Resources: H.; Data Curation: H.; Writing Original Draft Preparation: B.H.H., H., M.B., S.S., P., D.S., R.S., and R.W.A.; Writing Review and Editing: H., M.B., S.S., P., D.S., R.S., and R.W.A.; Visualization: B.H.H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] S. Goharinejad, M. N. Ahrari, K. Moulaei, and A. Sarafinejad, "Evaluating the effects of mobile application-based rehabilitation on improving disability and pain in patients with disputed Thoracic Outlet Syndrome: A randomized controlled trial," *International Journal of Medical Informatics,* vol. 185, no. 1, pp. 105400–105408, May 2024.

[2] L. K. Teubner, J. Henkel, and R. Bekkers, "Industry consortia in Mobile Telecommunications Standards Setting: Purpose, organization and Diversity," *Telecommunications Policy,* vol. 45, no. 3, pp. 102059–102066, Apr. 2021. doi:10.1016/j.telpol.2020.102059

[3] I. Havinga, D. Marcos, P. Bogaart, D. Tuia, and L. Hein, "Understanding the sentiment associated with cultural ecosystem services using images and text from social media," *Ecosystem Services,* vol. 65, no. 1, pp. 101581–101589, Feb. 2024. doi:10.1016/j.ecoser.2023.101581

[4] S. B. Haddi, A. Zugari, A. Zakriti, and S. Achraou, "Design of a band-stop planar filter for telecommunications applications," *Procedia Manufacturing,* vol. 46, no. 1, pp. 788–792, 2020. doi:10.1016/j.promfg.2020.04.006

[5] P. Srinuan, C. Srinuan, and E. Bohlin, "An empirical analysis of multiple services and choices of consumer in the Swedish Telecommunications Market," *Telecommunications Policy,* vol. 38, no. 5–6, pp. 449–459, Jun. 2014. doi:10.1016/j.telpol.2014.03.002

[6] T. Bi, P. Liang, A. Tang, and C. Yang, "A systematic mapping study on text analysis techniques in software architecture," *Journal of Systems and Software,* vol. 144, no. 1, pp. 533–558, Oct. 2018. doi:10.1016/j.jss.2018.07.055

[7] M. Uno, Y. Nakamaru, and F. Yamashita, "Application of machine learning techniques in population pharmacokinetics/pharmacodynamics modeling," *Drug Metabolism and Pharmacokinetics,* vol. 1, no. 1, pp. 101004–101011, Feb. 2024. doi:10.1016/j.dmpk.2024.101004

[8] M. J. Sánchez-Franco, F. J. Arenas-Márquez, and M. Alonso-Dos-Santos, "Using structural topic modelling to predict users'

sentiment towards intelligent personal agents. an application for Amazon's Echo and Google Home," *Journal of Retailing and Consumer Services,* vol. 63, no. 1, pp. 102658–102665, Nov. 2021. doi:10.1016/j.jretconser.2021.102658

[9] Z. Wei and S. Zhang, "A structured sentiment analysis dataset based on public comments from various domains," *Data in Brief,* vol. 53, no. 1, pp. 110232–110239, Apr. 2024. doi:10.1016/j.dib.2024.110232

[10] D. Krisbiantoro, S. Sarmini, and A. A. Rahmah, "Designing a Digital Marketing Strategy for UMKM Batik Jati Kusuma using the Sostac Method," *Int. J. Informatics Inf. Syst.,* vol. 6, no. 3, pp. 114–119, Sep. 2023

[11] J. Shi, W. Li, Q. Bai, Y. Yang, and J. Jiang, "Soft prompt enhanced joint learning for cross-domain aspect-based sentiment analysis," *Intelligent Systems with Applications,* vol. 20, no. 1, pp. 200292–200299, Nov. 2023. doi:10.1016/j.iswa.2023.200292

[12] J. Wang, J. Zeng, H. Wen, and Z. Hu, "Designing mobile operator's tariff package pricing scheme based on user's internet behavior," *Computer Communications,* vol. 211, no. 1, pp. 93–103, Nov. 2023. doi:10.1016/j.comcom.2023.07.025

[13] P. Savci and B. Das, "Prediction of the customers' interests using sentiment analysis in e-commerce data for comparison of Arabic, English, and Turkish languages," *Journal of King Saud University - Computer and Information Sciences,* vol. 35, no. 3, pp. 227–237, Mar. 2023. doi:10.1016/j.jksuci.2023.02.017

[14] L. Zhang, K. Hua, H. Wang, G. Qian, and L. Zhang, "Sentiment analysis on reviews of mobile users," *Procedia Computer Science,* vol. 34, no. 1, pp. 458–465, 2014. doi:10.1016/j.procs.2014.07.013

[15] S. H. Yun, Y. Kim, and M. Kim, "Quality-adjusted international price comparisons of Mobile Telecommunications Services," *Telecommunications Policy*, vol. 43, no. 4, pp. 339–352, May 2019. doi:10.1016/j.telpol.2018.09.001

[16] L. Aksoy, A. Buoye, P. Aksoy, B. Larivière, and T. L. Keiningham, "A cross-national investigation of the satisfaction and loyalty linkage for mobile telecommunications services across eight countries," *Journal of Interactive Marketing*, vol. 27, no. 1, pp. 74–82, Feb. 2013. doi:10.1016/j.intmar.2012.09.003

[17] T. Garín-Muñoz, T. Pérez-Amaral, C. Gijón, and R. López, "Consumer complaint behaviour in telecommunications: The case of mobile phone users in Spain," *Telecommunications Policy,* vol. 40, no. 8, pp. 804–820, Aug. 2016. doi:10.1016/j.telpol.2015.05.002

[18] F. Kang, J. A. Hauge, and T.-J. Lu, "Competition and mobile network investment in China's telecommunications industry," *Telecommunications Policy*, vol. 36, no. 10–11, pp. 901–913, Nov. 2012. doi:10.1016/j.telpol.2012.02.003

[19] C. P. Chen, J.-Y. Weng, C.-S. Yang, and F.-M. Tseng, "Employing a data mining approach for identification of mobile opinion leaders and their content usage patterns in large telecommunications datasets," *Technological Forecasting and Social Change,* vol. 130, no. 1, pp. 88–98, May 2018. doi:10.1016/j.techfore.2018.01.014

[20] E. D. Marques et al., "Geochemical mapping by stream sediments of the NW portion of Quadrilátero Ferrífero, Brazil: Application of the exploratory data analysis (EDA) and a proposal for generation of new gold targets in Pitangui Gold District," *Journal of Geochemical Exploration,* vol. 250, no. 1, pp. 107232–107239, Jul. 2023. doi:10.1016/j.gexplo.2023.107232

[21] A. Tawakuli, B. Havers, V. Gulisano, D. Kaiser, and T. Engel, "Survey:Time-Series Data Preprocessing: A survey and an empirical analysis," *Journal of Engineering Research,* vol. 1, no. 1, pp. 1–9, Mar. 2024. doi:10.1016/j.jer.2024.02.018

[22] F. Liu, G. Li, and H. Yang, "Application of multi-algorithm mixed feature extraction model in underwater acoustic signal," *Ocean Engineering,* vol. 296, no. 1, pp. 116959–116968, Mar. 2024. doi:10.1016/j.oceaneng.2024.116959

[23] S. Lalla, R. Lu, Y. Guan, and S. Zhang, "Bloomdt - an improved privacy-preserving decision tree inference scheme," *Journal of Information and Intelligence,* vol. 1, no. 1, pp. 1–7, Feb. 2024. doi:10.1016/j.jiixd.2024.02.003

[24] G. Wu, C. Li, L. Yin, J. Wang, and X. Zheng, "Compared between support vector machine (SVM) and Deep Belief Network (DBN) for multi-classification of Raman spectroscopy for cervical diseases," *Photodiagnosis and Photodynamic Therapy*, vol. 42, no. 1, pp. 103340–103348, Jun. 2023. doi:10.1016/j.pdpdt.2023.103340

[25] X. Zhang et al., "Improved random forest algorithms for increasing the accuracy of forest aboveground biomass estimation using sentinel-2 imagery," *Ecological Indicators,* vol. 159, no. 1, pp. 111752–111759, Feb. 2024. doi:10.1016/j.ecolind.2024.111752

[26] R. Kumar, "Recurrent context layered radial basis function neural network for the identification of Nonlinear Dynamical Systems," *Neurocomputing*, vol. 580, no. 1, pp. 127524–127532, May 2024. doi:10.1016/j.neucom.2024.127524